

## **ENERGY CONSERVATION BEHAVIOR: A CRITIQUE OF THE COST-MINIMIZATION MODEL, AND A REVIEW OF SOME ALTERNATIVE MODELS\***

**PAUL S. KOMOR**

*Center for Energy and Environmental Studies  
Princeton University  
Princeton, New Jersey*

**LYNA L. WIGGINS**

*Department of Civil Engineering  
Stanford University  
Stanford, California*

### **ABSTRACT**

Methods commonly used to predict the effects of energy conservation programs, such as end-use models and discount rate estimates, make implicit use of the rational microeconomic model. This model is weak as a descriptive model, due in part to the rationality assumption, the exclusion of nonfinancial goals, and the failure to differentiate between perceived and actual costs. This article critiques the discount-rate model, and provides empirical evidence supporting the rejection of this model. Alternative techniques for modeling individual conservation choice are discussed, including the diffusion of innovations model, the attitude-behavior model, and the marketing model.

### **INTRODUCTION**

Any non-mandatory residential energy conservation program is an attempt to influence individual behavior. For example, rebates for the purchase of energy-efficient appliances are intended to make these appliances more attractive to the consumer, and ultimately to influence purchasing decisions. Similarly, home energy audits are an attempt to improve the household's knowledge of energy

\* This research was conducted at Stanford University, and was supported in part by the UPS Foundation.

conservation, and to encourage the household to take appropriate energy conservation measures.

In order to predict the effects of an energy conservation program, it is necessary to have some understanding of individual behavior. Since a program's effects are a direct result of an individual behavior change, predictions of program effects can best be made with an understanding of how individuals make energy conservation choices. Most efforts at predicting energy conservation program effects are based upon the assumption of rational decision making. Consumers are modeled as utility-maximizers, acting in accordance with the microeconomic theory of consumer behavior. In practice, consumers are assumed to minimize life-cycle costs using an appropriate discount rate when making energy conservation decisions. This assumption of economically rational behavior is intuitively appealing, as it comes from a comprehensive and accepted theoretical background. However, there is a wealth of empirical evidence demonstrating that actual behavior does not conform to these theoretical predictions. These differences are not insignificant flukes, but persistent and robust phenomena. Since energy conservation programs are attempts to influence consumers, a model of these programs must reflect actual behavior, not inaccurate theoretical predictions of behavior.

This article will provide the following: an overview of existing techniques for predicting the impacts of residential energy conservation programs and a discussion of the assumptions underlying these techniques, a presentation of the evidence arguing against the validity of these assumptions, and a discussion of some alternative techniques which could be used to predict the effects of energy conservation programs.

## **OVERVIEW OF EXISTING TECHNIQUES**

This overview will focus on techniques which have used models of individual behavior to predict the impacts of conservation programs. To provide the necessary background, a short history of energy demand forecasting will be given.

### **History**

The first models of energy demand were based on aggregate estimates of income, price, and other relevant variables. For example, Houthakker proposed a model in which electricity consumption for the entire residential sector could be predicted by average values of income per household, marginal prices for gas and electricity, and household appliance holdings [1]. Similar models by Fisher and Kaysen and others were also based on average values for the entire residential sector [2]. The aggregate nature of these models did not lend itself to forecasting the effects of conservation programs. Of course, up until the early 1970s

there was little need for such forecasting. In the early 1970s, however, electric utilities faced an increasing marginal cost curve for new generation, and the need for more accurate demand forecasting became apparent. The first model based on disaggregate household data was that developed by Dole [3]. This type of model, called an end-use model, has become a popular tool for forecasting energy demand. As these models have improved, they have been increasingly used to address policy questions concerning the impacts of conservation programs.

### **End-Use Models**

Dole's end-use model was followed by the well-known Oak Ridge National Laboratory (ORNL) end-use model [4]. The treatment of consumer behavior in the ORNL model is straightforward: consumers are assumed to minimize life-cycle costs when making appliance choice decisions [5]. Weatherwax developed a microeconomic end-use model for use in forecasting residential peak electric load within a utility service area [6]. The California Energy Commission used a similar model to forecast energy demand [7].

The Electric Power Research Institute sponsored the development of an end-use model called the Residential End-Use Energy Planning System (REEPS). REEPS is a simulation model based on a nested logit probability structure. It uses individual household survey data to forecast energy consumption for the entire residential sector. Of all the end-use models, the REEPS model has the most sophisticated treatment of consumer behavior. Like the ORNL model, the REEPS model is based in part on the microeconomic theory of consumer behavior [8]. In determining appliance choice behavior, "households are assumed to be motivated to minimize the life-cycle cost of achieving specified levels of service" [8, pp. 3-9]. Household decisions are made by comparing capital and operating costs. Retrofits, such as insulation additions, can occur only as a response to an increase in energy prices [5, p. 96].

### **Discount Rate Estimates**

Because end-use models rely so heavily on costs and benefits as determinants of behavior, these models require as inputs the rate at which households trade off present and future costs. This tradeoff is usually expressed as a discount rate, which is simply the percent per year that future costs or benefits are reduced relative to present costs or benefits. A 5 percent discount rate means that \$1.00 received one year from now is valued the same as \$0.95 received now. Reasons commonly given for discounting the future include inflation, uncertainty of future costs or benefits, and opportunity costs.

The literature on discount rates in consumers' energy-related decisions is reviewed by Train [9]. There are essentially two different methods by which

discount rates have been estimated. The usual method is to fit a cost function to consumers' actual choices. For example, Hausman used a model of the form [10]:

$$\text{Air Conditioner Purchase Choice} = f(\text{operating costs, initial cost, discomfort}) \quad (1)$$

where "discomfort" is a measure of the amount of hot weather the user is willing to tolerate. The discount rate is calculated from the coefficients of the operating costs and purchase price variables. This type of analysis does not allow for control of all the other variables which affect appliance choice; such as discounted prices, installation costs, and product availability. A less common technique for determining discount rates is the use of experiments, in which a consumer's response to a hypothetical situation is used to calculate an implied discount rate. This technique allows the researcher to keep constant all other variables which could affect a consumer's decision. However, it fails to distinguish between actual behavior and self-reports of behavior. Both these types of analyses are directed at the same goal: determining the discount rate used by a consumer when making energy-related decisions. Both these analyses implicitly assume that a consumer's decisions are rational, and are based upon a goal of cost minimization.

### CRITICISM OF EXISTING TECHNIQUES

The use of a cost-minimization assumption in modeling consumer behavior can be criticized for a number of reasons, both theoretical and practical.

#### Criticism #1—Rationality Assumption

Rationality requires, in part, that preferences are transitive. That is, if there are three alternatives F, G, and H; then if F is preferred to G, and G is preferred to H, then F must be preferred to H. Transitivity of preferences seems like a reasonable requirement. However, consider the following counter-example [11]. You are hiring a new employee for the Acme Widget Company. There are three candidates, with the following qualifications:

<i>Name</i>	<i>IQ</i>	<i>Years Experience</i>
A	120	2
B	130	1
C	140	0

You prefer candidate B to candidate C, since experience is important, and a 10-point IQ difference is not significant. You also prefer candidate A to candidate B, since that extra year of experience is worth something, and again the 10-point

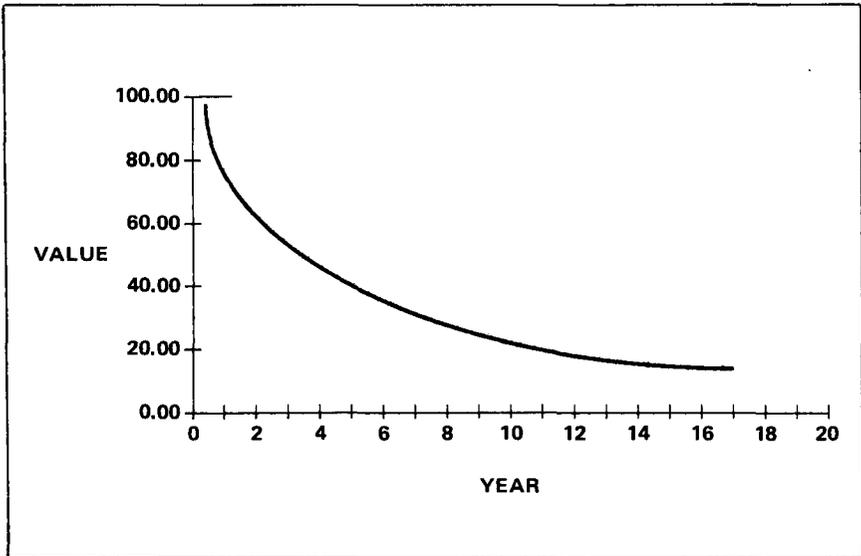


Figure 1. The discount-rate method.

IQ difference is meaningless. However, in comparing candidate A to candidate C, you are impressed by candidate C's 20-point IQ advantage, and decide this more than compensates for candidate C's inexperience. Therefore, you prefer candidate C to candidate A. You have just made an intransitive irrational choice. This choice can easily be criticized from a prescriptive viewpoint, but it can also easily be accepted as an example of what actually happens when real people make real decisions. This example does not disprove rationality. However, it does demonstrate a situation in which an intransitive decision seems quite reasonable. One could easily imagine other similar situations in which violations of the rationality assumptions are made.

### Criticism #2—Method Assumption

The use of a discount rate implies that each successive year is discounted by a set percent. For example, \$100 received each year for twenty years discounted at 10 percent per year is shown in Figure 1.

However, one could imagine decisions being made based on the following criteria: all returns more than three years away are ignored, simple payback must be less than five years, if it requires going into debt it's not done, or net cash flow must be positive within two years. These criteria may not be normatively appealing, but without empirical evidence supporting the use of the discount

rate method, there is no reason to accept the discount-rate method of financial decision making over the simpler criteria listed above.

Kempton and Montgomery used in-depth personal interviews to explore how consumers use simplified measurements for residential energy conservation decisions [12]. They found the following methods were common:

1. dollars, rather than kilowatt-hours or gallons (liters) of fuel oil, are used as a basis for comparison;
2. peak dollars (such as the largest bill received in a heating season), rather than average dollars, are used to compare yearly totals; and
3. simple payback, which is the initial cost divided by the first period's savings, is often used to judge an investment's attractiveness.

Consumers interviewed by Kempton and Montgomery did not appear to use a discount rate when making calculations.

As further evidence of the inappropriateness of the discount rate method as a descriptive model, consider the experimental data collected by Houston [13]. This experiment asked consumers how much annual savings they would require to invest \$100 in energy conservation. One-third of the survey respondents chose the "don't know" response. It therefore seems unlikely that the discount rate method is commonly used by consumers, given that 33 percent of a random sample were unable to use it even when specifically requested to.

### **Criticism #3—Exclusion of Other Goals**

The cost-minimization model typically expresses the utility ( $U$ ) of an alternative as:

$$U = f(\text{initial cost, operating cost, other terms}) \quad (2)$$

where the unspecified terms are an attempt to capture the effects of other factors that can influence choice. In practice, these terms are often ignored or given scant attention. Hausman, as discussed above, includes only a measure of discomfort as a supplemental term [10]. In the REEPS model, "a household selects appliance efficiency in a manner which trades off incremental appliance purchase price against expected operating cost" [5, p. 95]. This formulation assumes that the primary goal of the consumer is to minimize expenditures, and the only relevant factors are initial costs and operating costs. However, a consumer may be attempting to satisfy a number of different goals, all of which may influence decisions. Wilk and Wilhite, in a study of weatherization behavior, define a number of goals which interviewees pursue when making energy-related decisions [14]. These include independence or self reliance, desire to preserve resources, and "building a safe and secure haven for the family" [14, p. 628]. Other researchers have placed great emphasis on the role of social networks and

peer group influences in decision making [15, 16]. The cost-minimization formulation ignores all these influences.

#### **Criticism #4—Perceived Costs**

Cost-minimization models typically use actual values for initial and operating costs. Initial costs are often based on manufacturer's price lists (which do not reflect installation costs), and operating costs are based on engineering estimates reflecting actual energy prices and expected use patterns. Consumers, however, do not make decisions based on actual costs. Rather, they make decisions based on what they know—that is, the perceived costs. There is often a wide disparity between actual and perceived costs.

In a study of forty-three well-educated households in Princeton, few could accurately give the price of a kilowatt-hour of electricity. Answers ranged from \$0.03 to \$5.00, with a median of \$0.31. The correct answer was \$0.05, but only 16 percent guessed \$0.10 or under [12].

It is unrealistic to assume consumers will make complex calculations of operating costs if they are unaware of basic information such as electricity prices.

#### **Criticism #5—Empirical Results**

One test of a model is the validity of its assumptions. Criticisms #1 and #2 above argue that the assumptions behind the rational model, as it is commonly used in conservation impact forecasting, are not valid as a descriptive model. However, a model may also be judged by its accuracy. That is, a model that works is valuable, whether or not its assumptions are valid. If the discount-rate model can accurately predict behavior, then it may be irrelevant that its assumptions are inaccurate. Few claim that consumers actually think in terms of a discount rate, but that consumer's actions imply a discount rate that can be used to predict behavior. So we now turn to the evidence: does the model work?

Any consumer energy conservation decision can be said to imply a discount rate. A conservation decision has an initial cost and an operating cost. By making some assumptions about inflation, fuel price changes, salvage value, and product life; one can always calculate an implied discount rate. The question is not whether this rate exists, it is whether or not it is useful in modeling conservation decisions. Estimates for implied discount rates show a very high variation: from 3.7 percent [17] to 300 percent [18]. This high variation makes it extremely difficult for an energy planner trying to predict program impacts by assuming a mean discount rate. Typically one must arbitrarily select a rate that sounds reasonable, with no guarantee of descriptive accuracy. The high variation in empirical discount rate estimates makes the discount-rate model difficult to use in conservation program impact forecasting.

Table 1. Implied Discount Rates from the Palo Alto, California Survey Data

<i>Conservation Action</i>	<i>Mean Implied Discount Rate (Percent)</i>	<i>Standard Deviation (Percent)</i>	<i>Sample Size</i>	<i>Minimum (Percent)</i>	<i>Maximum (Percent)</i>
Insulation	3	45	91	-38	375
Caulk	63	91	80	-24	600
Showerhead	129	270	78	-28	1500
Thermostat	42	63	105	-24	375

To further evaluate the discount-rate model, data on residential energy user's perceptions of the costs and savings of conservation were collected. A survey was sent by mail to 1000 households in Palo Alto, California. These households were randomly selected from electric utility billing records, and the response rate to the survey was 48.7 percent.<sup>1</sup> Respondents were asked for their perceptions of the costs and savings of four typical energy conservation actions: ceiling insulation, caulking, a low-flow showerhead, and a clock (setback) thermostat. In addition, respondents were asked if they had installed these conservation measures in their residences. If a respondent had not installed a measure, then the associated costs and savings estimates were then used to calculate a minimum discount rate.

To clarify the concept of a minimum discount rate, consider the example of ceiling insulation. If a survey respondent indicated that he or she had not installed ceiling insulation, then according to the discount-rate model of behavior this decision was reached because the respondent believed that the discounted savings were not large enough to justify the costs. Since the perceived costs and savings were given by the respondent, the implied discount rate represents a minimum discount rate. It is known that the respondent discounts the savings such that the present value of the savings are at best equal to the cost. The discount rate may be higher, but we know that it is not lower.

Table 1 shows the mean discount rates for respondents for the four conservation actions. For each of the four actions, the costs and savings estimates for those respondents who did not take the action were used to calculate an implied minimum discount rate. This discount rate was calculated using standard accounting equations. Cost ( $C$ ) was equated to the present value of the savings  $PV[S]$ :

$$C = PV[S] = S * \left[ \frac{(1+i)^n - 1}{i * (1+i)^n} \right], \quad (3)$$

<sup>1</sup> A copy of the survey instrument and further information on the sampling technique can be found in [19].

where  $i$  is the implied discount rate,  $S$  is the annual savings, and  $n$  is the duration of the savings.<sup>2</sup> Equation (3) was solved iteratively for  $i$  for each respondent.

As Table 1 shows, implied consumer discount rates (if they can be said to exist at all) vary widely. For example, those survey respondents who did not install a low-flow showerhead had a mean discount rate of 129 percent. The huge standard deviations show the inaccuracy inherent in using a mean discount rate, and the irrationally high mean discount rates for all but insulation make a strong argument for the rejection of discount rates as a method of predicting consumer choice.

### Summary

Most efforts at predicting conservation program impacts are based on the microeconomic theory of consumer choice. Consumers are characterized as utility maximizers, and in practice are modeled as cost-minimizers. The use of the cost-minimization model implies the use of a discount rate, which is used to reduce the value of future costs or benefits. The use of this model can be criticized on a number of points: utility maximization requires the assumption of transitivity of preferences, which may not be an accurate descriptive assumption; the use of a discount rate implies that each succeeding year's costs or benefits are reduced by a set percentage, and there is empirical research by Houston implying that consumers often do not use this method in making energy-related decisions [13]; cost-minimization models typically do not account for goals other than strictly financial ones; cost-minimization models do not differentiate between actual costs and perceived costs; and estimates for implied discount rates show a very high variation. The cost-minimization model, although normatively appealing, cannot be defended as an accurate descriptive model of conservation behavior.

## ALTERNATIVE THEORIES

There are a number of alternatives to the microeconomic theory of consumer choice. These alternatives are fundamentally different from the microeconomic theory in that they are intended and designed as descriptive models of individual choice. They express no judgment and give no guidelines concerning how decisions should be made. Rather, they look for patterns in individual behavior and attempt to generalize these patterns into a descriptive model. This section will discuss three frameworks for individual choice: the diffusion of innovations model, the attitude-behavior model, and the marketing model. Each model will be briefly described, and its applicability to modeling energy conservation choice will be discussed.

<sup>2</sup> Table 1 reflects a 10-year savings duration. Calculations were made for  $n = 5, 10,$  and  $20$  years; the results are not very sensitive to  $n$ . Results for all three  $n$  assumptions can be found in [19].

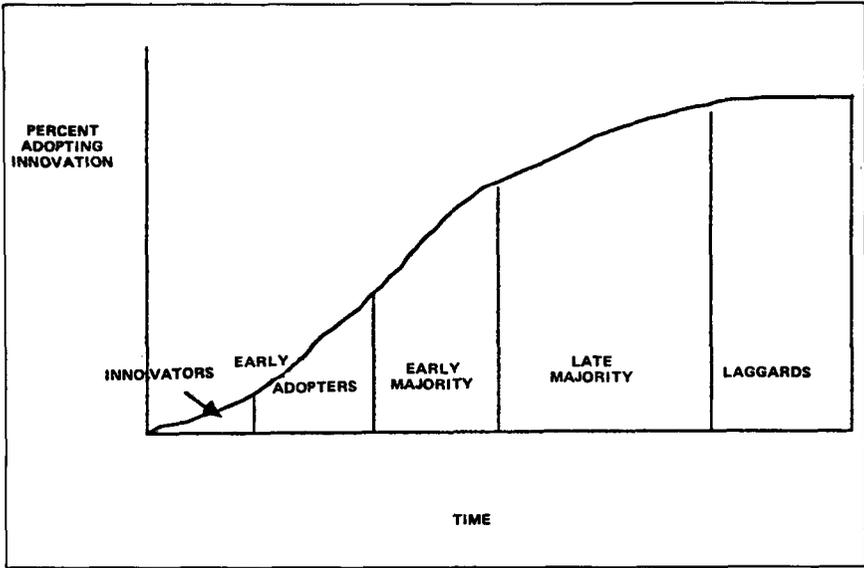


Figure 2. S-shaped adoption curve [16].

### Diffusion of Innovations

In 1954, a study of home air conditioner use uncovered some curious patterns in air conditioner purchases. On average, about 24 percent of the households in the study had air conditioners. However, this number varied widely; some blocks had almost no air conditioners, while other blocks had over 30 percent. This variation in an otherwise homogeneous neighborhood was attributed to the existence of a strong communication network, where decisions to purchase air conditioners were heavily influenced by interpersonal communication.

Evidence of this sort is often identified with the diffusion of innovations framework [16]. This model emphasizes the importance of informal communication networks as influences on the diffusion of new technologies, methods, or ideas. Rogers and Shoemaker identify five characteristics of an innovation which determine its rate of adoption:

1. relative advantage—the degree to which an innovation is perceived as being better than the item it replaces;
2. value compatibility—the match between the innovation and the adoptee's values;
3. complexity—the perceived difficulty in use and understanding of the adoption;

4. trialability—the degree to which the innovation can be tested before total commitment; and
5. observability—the visibility of the innovation's outcomes.

Rogers segments the target population by its innovativeness (Figure 2).

There have been a number of applications of this model to residential energy conservation [20-24]. Leonard-Barton found that a strong predictor of solar adoption was the number of acquaintances who owned such equipment [25]. Puget Sound Power and Light Co. found that adoption of wood heating and fireplace inserts did follow an S-shaped curve [21].

Energy conservation research utilizing the diffusion of innovations framework has emphasized the role of social networks. The relative success of various conservation programs has been attributed to their use of informal communication networks [20]. However, the diffusion of innovations framework has not been used in a quantitative sense to either predict or evaluate the effects of conservation programs. This is due in part to the qualitative nature of the framework. The innovation categories (such as laggards) have yet to be well-defined enough to allow classification of target populations based on these categories. The framework can be useful for program design, but it is too general for use in prediction or evaluation.

### **Attitude-Behavior Models**

Some energy researchers have borrowed the concept of attitude from social psychology. The results of applying this concept to individual conservation behavior have been mixed, due in part to an incomplete understanding of the relationship between attitude and behavior. This section will briefly outline the field of attitude-behavior research, and will discuss applications to energy conservation behavior.

Much of the effort in attitude-behavior research has been directed at understanding the link between attitude and behavior. Numerous studies have attempted to predict behavior by measuring attitudes, with disappointing results. This is due to problems in measurement, definition, and theory. Early definitions of attitude implied that behavior followed from attitudes. Allport defined attitude as, "exerting a directive of dynamic influence upon the individual's response" [26]. However, an abundance of empirical research indicated that the link between attitude and behavior was somewhat more tenuous than previously thought [27]. In an extensive review of empirical research, Wicker concluded, "these studies suggest that it is considerably more likely that attitudes will be unrelated or only slightly related to overt behaviors" [28, p. 65]. According to Ajzen and Fishbein, "the general consensus was that measures of attitude have little value for the prediction of overt behaviors" [15].

Recent work has indicated that attitude is related to behavior, but that other factors, including perceived social norm and situation variables, can also

influence behavior. Ajzen and Fishbein argue that, "strong attitude-behavior relations are obtained only under high correspondence between at least the target and action elements" [15, p. 888]. In other words, a specific directed attitude will better predict behavior than a general undirected attitude. One would expect answers to the question: How do you feel about your conserving energy in your home? to better predict conservation behavior than the question: How do you feel about energy conservation? Ajzen and Fishbein also attribute low attitude-behavior correlation to poor measurements and definitions of attitude and behavior.

The attitude-behavior framework has been applied to energy conservation behavior with limited success. The typical application involves first a collection of attitudinal survey data, followed by factor analysis to extract the relevant attitudes, and then use of the factors to predict behavior or intent. Seligman *et al.* used data from an attitudinal survey of fifty-six couples in New Jersey to see if attitudes could predict electricity consumption [29]. In order to dimensionally reduce the attitudinal data, factor analysis was used. Four factors (listed in order of decreasing predictive power) emerged, which were termed: personal comfort and health; high effort/low payoff; role of the individual; and legitimacy of the energy crisis. These four factors were used in a multiple regression to predict electricity consumption.

Leonard-Barton used an index measuring, "an individual's tendency toward a lifestyle of voluntary simplicity," to predict investments in energy conservation [25]. Using survey data from Palo Alto, California, Leonard-Barton used factor analysis to find factors termed material simplicity, self-determination, and ecological awareness. These factors were used to predict investments in energy-conserving equipment. Overall correlations were not given, but the voluntary simplicity lifestyle was found to be a strong predictor.

To summarize, there is no widely accepted definition of attitude, and the link between attitude and behavior is not well understood. Attitudes are difficult to measure, and data on target behaviors are often unavailable. As in the diffusion of innovations framework, attitude-behavior research has not yet developed to the extent that it can be used to quantitatively predict or evaluate the impacts of conservation programs.

## Marketing Model

The field of marketing covers many areas. This section will cover only selected research on consumer decision making. Although there is no overall unifying theory or model of consumer decision making, there has been extensive research on how decisions are made. Much of this research is relevant to energy conservation decision making. Research on behavioral decision making from a marketing perspective can be divided into two areas: strategies and attributes. Strategies are the methods consumers use to evaluate alternatives, given a set of relevant characteristics. One possible strategy is to

pick one characteristic, such as price, and select the alternative which performs best on that alternative, that is the lowest price alternative. Attributes are the variables or characteristics which affect choice. Examples include price, availability, or visual appeal. To further clarify these two concepts, choice can be represented by a function:

$$\text{Choice} = f(X). \quad (4)$$

Strategies are the function  $f$ , while attributes are the vector  $X$ . This section will review the evidence on both strategies and attributes.

*Strategies* – One method for trading off dissimilar attributes might be to assign a utility  $U(i)$  to an alternative  $i$  by taking the sum of the products of the attributes  $X_k$  and the weights  $W_k$ :

$$U(i) = \sum_k W_k * X_k. \quad (5)$$

There are many other ways that alternatives could be compared. Some other possible strategies include:

1. affect referral, in which consumers elicit from memory a previously formed overall evaluation—an example of this strategy in use by a consumer making a decision to purchase a car is the statement, “my last car was good—I’ll buy another just like it”;
2. lexicographic, in which attributes are first ordered in terms of importance, and the alternative with the highest level of the most important attribute is chosen—an example is, “I want the cheapest car I can find”; and
3. conjunctive, in which an alternative is acceptable only if it exceeds minimum cutoffs  $X_{\min}$  for all attributes  $X$ —an example is, “I’ll only consider cars with mileage over 30 mpg and that cost less than \$7000.”

There are many other possible strategies. Bettman defines ten distinct strategies that consumers use at various times when making choices [30].

Market researchers have used some ingenious techniques to determine when and under what conditions consumers use different strategies. The simplest technique is the correlational method, in which consumers are simply asked for their evaluations of each attribute of an alternative, and also for their overall evaluations of each alternative. The results are fit to an equation using statistical techniques such as multiple regression. This method assumes a holistic evaluation of an alternative. Another technique is the protocol method, in which an experimental subject is presented with a set of alternatives and is instructed to think out loud while examining them. Data from this type of analysis are difficult to code, and the results may suffer from self-censoring bias. Eye-movement analysis, in which a subject’s eye movements are tracked as they examine attributes and alternatives, has been used by a few researchers. This avoids self-censoring bias; but the equipment is expensive and obtrusive, and data are again difficult to code.

Results of strategy research have been mixed. As one might expect, consumers appear to use different strategies at different times. Factors affecting the choice of strategy include: difficulty and complexity of task, individual characteristics, time pressure to make choice, distractions, extraneous data, and incomplete data. No firm rules have been found, but several useful general conclusions can be made: consumers operate under a constraint of limited cognitive capacity [31], and the linear compensatory model has relatively high predictive accuracy.

*Attributes* – When making a choice, what attributes do consumers consider? Surprisingly, research of this type is relatively rare. In some research situations, consumers are presented with a set of attributes (cost, quality, etc.) and asked to make a choice. This situation allows consumers to use only the restricted set of attributes made available to them, and of course excludes from consideration attributes not presented. Surveys of the type, “How important was attribute *X* in your decision . . .” suffer from saliency bias, in which the increased saliency of the suggested attribute can affect the response. Because of these complications, and because the set of attributes *X* is so heavily dependent on the specific set of alternatives being considered, very little research has been done on defining the attribute vector *X*.

Applications of marketing research to energy conservation choice is limited by marketing research’s emphasis on choice between comparable alternatives. Marketing research has focused on understanding how consumer choose between college A and college B [32], or apartment X and apartment Y [33]. Energy conservation choices, however, are rarely between insulation A and insulation B.<sup>3</sup> Rather, the choice is between alternatives (such as installing weatherstripping or going to the beach) that are not directly comparable. There has been limited market research on noncomparable alternatives [34]. However, this is the exception, and the application of market research theory and evidence to energy conservation choice will be limited by energy conservation’s special role as a choice between noncomparable alternatives.

## SUMMARY

Techniques commonly used to predict the effects of conservation programs, such as end-use models and discount rate estimates, make implicit use of the rational microeconomic model. This model is weak as a descriptive model, due in part to the rationality assumption, the exclusion of nonfinancial goals, and the failure to differentiate between perceived and actual costs. Alternative techniques for modeling conservation choice include the diffusion of innovations model [16], the attitude-behavior model [15], and the marketing model [30]. These three models can be considered behavioral models, as they attempt to describe actual behavior.

<sup>3</sup> These choices are made, of course, but they are not of primary interest to us.

Of these three models, the diffusion of innovations model offers the most complete incorporation of the role of social forces in influencing behavior. However, this model is not directly applicable to energy conservation, due to the need for quantitative models of conservation programs. The attitude-behavior model is inherently appealing, yet it suffers from a poor predictive record. It is not clear if this poor record is due to the model itself or to the conditions under which it has been evaluated, but in any case it does not offer the quantitative analysis needed for conservation program modeling. The marketing model, although it lacks a grand unifying theory, offers the concepts of strategies and attributes, which are applicable to energy conservation modeling.

### REFERENCES

1. H. S. Houthakker, Some Calculations of Electricity Consumption in Great Britain, *Journal of The Royal Statistical Society, A*:3, 1951.
2. F. Fisher and C. Kaysen, *A Study in Econometrics: The Demand for Electricity in the U.S.*, North-Holland, Amsterdam, 1962.
3. S. Dole, *Energy Use and Conservation in the Residential Sector*, Report R-1641-NSF, RAND, Santa Monica, CA, 1975.
4. E. Hirst and J. Carney, *The ORNL Engineering-Economic Model of Residential Energy Use*, Report ORNL/C0N-24, Oak Ridge National Laboratories, Oak Ridge, TN, 1978.
5. T. Cowing and D. McFadden, *Microeconomic Modeling and Policy Analysis*, Academic Press, Orlando, FL, 1984.
6. R. Weatherwax and C. York, *An Historical Review of End-Use Models*, California Energy Commission, Sacramento, CA, 1980.
7. California Energy Commission, *Energy Demand Forecasting Issues*, Report P300-85-020, Sacramento, CA, December 1985.
8. A. Goett and D. McFadden, *Residential End-Use Energy Planning System*, Report EA-2512, Electric Power Research Institute, Palo Alto, CA, July 1982.
9. K. Train, Discount Rates in Consumers' Energy-Related Decisions, *Energy, the International Journal*, 10:12, p. 1243, 1985.
10. J. Hausman, Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables, *Bell Journal of Economics*, 10:1, p. 33, 1979.
11. Amos Tversky, personal communication, class Psy. 156, fall 1985.
12. W. Kempton and L. Montgomery, Folk Quantification of Energy, *Energy, the International Journal*, 7:10, p. 817, 1982.
13. D. Houston, Implicit Discount Rates and the Purchase of Untried, Energy-Saving Durable Goods, *Journal of Consumer Research*, 10, p. 236, 1983.
14. R. Wilk and H. Wilhite, Why Don't People Weatherize Their Homes?: An Ethnographic Solution, *Energy, the International Journal*, 10:5, p. 621, 1985.
15. I. Ajzen and M. Fishbein, Attitude-Behavior Relations, *Psychological Bulletin*, 84:5, p. 888, 1977.
16. E. Rogers and W. Shoemaker, *Communications of Innovations*, Free Press, New York, NY, 1971.

17. R. Johnson, *Housing Market Capitalization of Energy-Saving Durable Good Investments*, Report ORNL/CON-74, Oak Ridge National Laboratories, Oak Ridge, TN, 1981.
18. D. Gately, Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables: Comment, *Bell Journal of Economics*, 11:1, p. 373, 1980.
19. P. Komor, *Residential Energy Conservation: A Descriptive Model of Individual Choice*, doctoral dissertation, Resources Planning Program, Department of Civil Engineering, Stanford University, Stanford, CA, 1987.
20. S. Coltrane, D. Archer, and E. Aronson, The Social-Psychological Foundations of Conservation Programmes, *Energy Policy*, 14:2, p. 133, 1986.
21. Puget Sound Power and Light Co., *Alternative Energy Project Report*, Bellevue, WA, May 1983.
22. J. Darley, Energy Conservation Techniques as Innovations, and Their Diffusion, *Energy and Buildings*, 1, p. 339, 1977/78.
23. J. Darley and J. Beniger, Diffusion of Energy-Conserving Innovations, *Journal of Social Issues*, 37:2, p. 150, 1981.
24. A. Shama, Energy Conservation in U.S. Buildings, *Energy Policy*, 11:2, p. 148, 1983.
25. D. Leonard-Barton, Voluntary Simplicity Lifestyles and Energy Conservation, *Journal of Consumer Research*, 8, p. 243, 1981.
26. G. Allport, Attitudes, in *Handbook of Social Psychology*, C. Murchison (ed.), Clark University Press, Worcester, MA, 1935.
27. R. Petty and J. Cacioppo, *Attitudes and Persuasion*, Wm. C. Brown, Dubuque, IA, 1981.
28. A. Wicker, Attitudes Versus Actions, *Journal of Social Issues*, 25, 1969.
29. C. Seligman, J. Darley, and L. Becker, Behavioral Approaches to Residential Energy Conservation, *Energy and Buildings*, 1, p. 325, 1977/78.
30. J. Bettman, *An Information Processing Theory of Consumer Choice*, Addison-Wesley, Menlo Park, CA, 1979.
31. J. March, Bounded Rationality, Ambiguity, and the Engineering of Choice, *Bell Journal of Economics*, 9, 1978.
32. P. Wright and M. A. Kriewall, State-of-Mind Effects on the Accuracy with Which Utility Functions Predict Marketplace Choice, *Journal of Marketing Research*, 17, 1980.
33. J. Payne, Task Complexity and Contingent Processing in Decision Making, *Organizational Behavior and Human Performance*, 16, p. 366, 1976.
34. M. Johnson, Consumer Choice Strategies for Comparing Noncomparable Alternatives, *Journal of Consumer Research*, 11, p. 741, 1984.

Direct reprint requests to:

Paul S. Komor  
 Center for Energy and Environmental Studies  
 Princeton University  
 Princeton, NJ 08544